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ACM
2020

Back , P , Suominen , A , Malo , P , Tahvonen , O , Blank , J & Deb , K 2020 , Towards Sustainable Forest Management Strategies with MOEAs . in GECCO '20 : Proceedings of the 2020 Genetic and Evolutionary Computation Conference . ACM , New York , pp. 1046-1054 , Genetic and Evolutionary Computation Conference , Cancún , Mexico , 08/07/2020 . https://doi.org/10.1145/3377930.3389837

http://hdl.handle.net/10138/329099
https://doi.org/10.1145/3377930.3389837

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acceptedVersion

Towards Sustainable Forest Management Strategies with MOEAs

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COIN Report Number 2020014

Abstract

Sustainable forest management is a crucial element in combating climate change, plastic pollution, and other unsolved challenges of the 21st century. Forests not only produce wood – a renewable resource that is increasingly replacing fossil-based materials – but also preserve biodiversity and store massive amounts of carbon. Thus, a truly optimal forest policy has to balance profit-oriented logging with ecological and societal interests, and should thus be solved as a multi-objective optimization problem. Economic forest research, however, has largely focused on profit maximization. Recent publications still scalarize the problem a priori by assigning weights to objectives. In this paper, we formulate a multi-objective forest management problem where profit, carbon storage, and biodiversity are maximized. We obtain Pareto-efficient forest management strategies by utilizing three state-of-the-art Multi-Objective Evolutionary Algorithms (MOEAs), and by incorporating domain-specific knowledge through customized evolutionary operators. An analysis of Pareto-efficient strategies and their harvesting schedules in the design space clearly shows the benefits of the proposed approach. Unlike many EMO application studies, we demonstrate how a systematic post-optimality trade-off analysis can be applied to choose a single preferred solution. Our pioneering work on sustainable forest management explores an entirely new application area for MOEAs with great societal impact.

Keywords: Economic forest research, optimal forest management, multi-objective optimization, NSGA-II, NSGA-III, MOEA/D

1 Introduction

The optimal management of forest resources has been debated for centuries. Early forestry regulations were designed to curb short-sighted selective logging ("harvest the best, leave the rest") and to guarantee a regular flow of timber [34]. But times have changed: climate change, plastic pollution, and biodiversity loss demand a multi-dimensional approach that can balance profit-oriented logging with ecological and societal interests. After all, forests represent multi-use resources that are highly valuable beyond their raw materials, e.g. for carbon storage, species and habitat diversity, and recreational purposes. Forest-related policies are thus not made by a single person with a single utility function, but involve multiple stakeholders with diverse objectives. The case of Finland, Europe's most forested country, exemplifies this conundrum: vast forests remove approx. 45% of Finland's annual CO_2 emissions and are thus paramount for reaching the government's ambitious goal to balance carbon sink and emissions by 2035; however, any reduction in timber harvesting - while lowering carbon emissions - would require painful economical and societal concessions as the Finnish forest industry accounts for 21% of the country's export revenues, and directly and indirectly employs 15% of the Finnish workforce. When negotiating such conflicting interests (here carbon storage vs. profit), people's preferences are not inherently fixed but may be softly defined and thus negotiable to a certain degree. Opposing policy makers may achieve compromises easier if the trade-off between conflicting interests could be quantified and visualized. For example, even a politician who puts economic growth above all else may be willing to sacrifice a little money if a disproportionately huge positive effect on biodiversity could be shown.

Economic forest research, however, has largely taken the perspective of forest owners. Finding optimal strategies thus corresponds to maximizing the forest's Net Present Value (NPV). Recent publications admittedly stress the importance of additional non-profit objectives, but scalarize the problem *a priori* by assigning weights to each objective [32]. In contrast, our approach allows us to assign the preferences for different objectives *a posteriori* by uncovering the Pareto-efficient frontier. Moreover, the authors in [32] report a run time of 50-120 hours for finding a single optimal forest management strategy. Uncovering the Pareto-efficient frontier - the set of potentially thousands of strategies that represent different yet optimal trade-offs - becomes computationally unfeasible with existing methods. Although multi-objective optimization has shown to solve such high-dimensional problems quickly and efficiently, it has not been applied in the forest management domain yet.

In this paper, we therefore assume the perspective of a policy maker and propose the use of Evolutionary Algorithms (EA) for finding a set of Pareto-optimal forest policies that may help to mitigate conflicting interests between stakeholders. Our approach differs from existing work in that it i) allows us to consider multiple different objectives simultaneously, and ii) provides the ability to express preferences a posteriori. Our work contributes a tool that:

- uncovers the Pareto-efficient frontier in a fraction of the time that it takes existing solutions to find a single strategy,
- aids in negotiating conflicting interest by visualizing the trade-offs between objectives, and
- prescribes the optimal harvesting schedule corresponding to each point on the non-dominated front to forest managers.

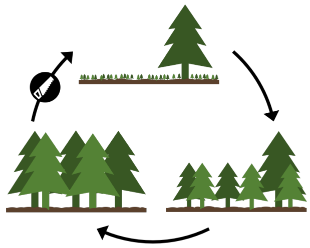
The rest of this paper is organized as follows. Section 2 discusses relevant research on the optimization of harvesting strategies under different forest management styles. Next, Sections 3, 4, and 5 present our problem formulation, methodology and findings. Finally, we provide conclusions and future directions in Section 6.

2 Related work and contributions

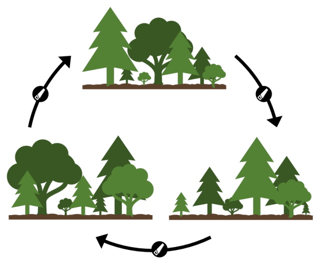
Before we present our EA approach for multi-objective forest strategy optimization, we provide some background on related forest economic research.

2.1 Earlier Research on Forest Management

In the Nordic countries two types of forest management strategies are currently in use: rotation forestry (RF) and continuous cover forestry (CCF).[1]



(a) Rotation forestry (RF)



(b) Continuous cover forestry (CCF)

Figure 1: Illustration of tree stand development under different forest management regimes.

Rotation forestry (Figure 1a) has been the dominating strategy across Fennoscandia since the 50's and follows a clear and repetitive cycle of artificial regeneration, growing, thinning, and final clear-cut harvesting that only leaves a few live retention trees. Economic models for RF build on various extensions of Faustmann's work from 1849 [14] that optimizes the interval length between clearcuts to maximize the timber yield. This single-objective setup leaves little room for environmental concerns. Numerous studies have shown the adverse ecological effects of clear-cut harvesting that irreversibly destroys natural forest characteristics, ruins habitat diversity, and removes trees as an inexpensive form of carbon storage.

Continuous cover forestry (Figure 1b) offers a more sustainable alternative that uses selection cutting (thinnings) to harvest individual trees of different sizes and species uniformly from the stand. Harvesting occurs more frequently but less intense which helps to preserve natural forest characteristics. Trees and soil store carbon more efficiently under CCF, so that this strategy even contributes towards combating climate change [1, 16]. However, economic models for CCF become more complex as they need to optimize not only the timing of partial harvesting (binary variable; similar to the clearcut intervals in RF), but also the number of trees harvested per size class *and* per species (continuous variable).[2]

[1] RF and CFF are often also referred to as even- and uneven aged forestry respectively due to the even/uneven tree age structure that these harvesting regimes produce.

[2] Species in the boreal forest typically include spruce, birch, pine,

In light of CCF's ecological advantages, it is unsurprising that the Nordics and the UK have recently seen a growing public interest in switching from ecologically harmful clear-cut harvesting to sustainable selection cutting [2]. The common misconception, shared by private forest owners and experts alike, that CCF would result in lower timber production [33] has been debunked by numerous studies that found RF and CCF fully competitive; see e.g. [20, 19, 21, 15, 22]. CCF becomes especially favorable when considering the economic value of forests beyond pure timber production, e.g. for recreational purposes, carbon storage, and biodiversity [32].

2.2 Finding Optimal Forestry Strategies

Finding optimal forest management strategies presents a dynamic discrete-time control problem. Complications arise from discontinuities, nonconvexities, a large number of decision variables, and the mixed-integer nature of the optimization problem (harvest timing variables are boolean; harvest amounts are continuous). Current state-of-the-art models can simultaneously cover RF and CCF regimes. In [32], Tahvonen et al. extend earlier results of [31] and apply bilevel optimization [7]: while keeping the harvest timings fixed, the lower-level uses gradient-based interior-point algorithms in AMPL/Knitro [4] to optimize the number of trees harvested per size class and species. The maximized objective value of the lower-level problem is then passed to a genetic algorithm [12, 30] in the upper-level to optimize the harvest timing vector.

This approach is well suited for single-objective studies that compare the economic performance of RF and CCF. However, it is unsuited for optimizing multiple objectives simultaneously due to the inherent limitations of the AMPL/Knitro optimizer that only supports single objective function. In their study on profitability and biodiversity, Tahvonen et al.[32] scalarize the problem by a priori assigning prices to different objectives, resulting in a weighted sum that can be solved via single-objective optimization. Similarly, the authors in [1] use the same bilevel approach as in [32] and assign a fixed carbon price before optimizing the total economic value. The method in [32] is computationally inefficient as the Knitro optimizer on the lower-level is called numerous times. The authors report 50-120 hours for a full iteration using an Intel (R) Xeon (R) E5-2643 v3 @3.40GHZ, 24 logical processing computer. In contrast, MOEAs can solve the optimization problem significantly faster and the speed does not vary much from single- to multi-objective cases.

3 Problem Formulation

Before optimizing forestry strategies with MOEAs we formulate the problem in an ecologically sound, yet mathematically tractable way. We utilize a size-structured forest growth model by Pukkala et al. [27] which has been estimated from empirical Finnish forest data. The model is widely used in economic forest research (see e.g. [32, 31, 1]), and includes functions for ingrowth, natural mortality, and diameter increment in mixed-species stands. Given the scope and limitation of this paper, we focus on the functions that are essential for the underlying problem formulation. We refrain from describing all functions, e.g. for ingrowth ϕ, stand growth α, and natural mortality μ in detail. Their exact formulation lays within the domain of forestry research and is thus besides the point of this work on MOEAs. For more information we kindly refer the reader to Appendix A (based on [27, 26, 1]) that contains detailed formulas and the numerical parameter values that were used in our experiments.

We discretize time into intervals of Δ years and denote these time steps by $t = t_0, t_0 + 1, ..., T$. We denote the number of trees in size class s at beginning of period t by $x_{st}, s = 1, 2, ..., n, t = t_0, t_0 + 1, ..., T$, where n is the number of size classes. For any point in time t, the forest stand structure can thus be given as $x_t = (x_{1t}, x_{2t}, ..., x_{nt})$. The fraction of trees that grow to the next size class $s + 1$ during each period t is given by $0 \leq \alpha_s(x_t) \leq 1, s = 1, ..., n - 1$, while the fraction of trees that die during each period t is denoted by $0 \leq \mu_s(x_t) \leq 1, s = 1, ..., n$. Hence, the fraction of trees that remain in the same size class during period t equals $1 - \alpha_s(x_t) - \mu_s(x_t) \geq 0$. Natural regeneration (i.e. trees entering the smallest size class) is given by the ingrowth function ϕ, with stand state x_t as its argument. We let h_{st} denote the number of trees in size class s that are harvested at the end of each time period t, and let $h_t = (h_{1t}, h_{2t}, ..., h_{nt})$. The stand development can therefore be given as

$$x_{1,t+1} = \phi(x_t) + [1 - \alpha_1(x_t) - \mu_1(x_t)]x_{1t} - h_{1t}, \quad (1)$$

$$x_{s+1,t+1} = \alpha_s(x_t)x_{st} + [1 - \alpha_{s+1}(x_t) - \mu_{s+1}(x_t)]x_{s+1,t} - h_{s+1,t}, \quad (2)$$

where $s = 1, ..., n - 1, t = t_0, ..., T$, and x_{t_0} is a given initial state at t_0 after a clear-cut and subsequent artificial regeneration. For the definitions of ϕ, μ, and α please see Appendix A. The harvested amounts also have to satisfy

$$0 \leq h_t \leq x_t. \quad (3)$$

3.0.1 Economic Value

Harvesting revenues for thinning and clearcut are given by $R(h_t)$ and $R(x_T)$, and harvesting costs by $C_{th}(h_t)$ and $C_{cc}(x_T)$, respectively. The cost from artificial regeneration (i.e. NPV of costs of all operations on the stand after clearcut but before t_0) is denoted by $w \geq 0$. All revenues and costs are given in €ha^{-1}. The discrete time discount factor is $b^\Delta = 1/(1+r)^\Delta$, where r is the interest rate and Δ is the length of the period. Because of fixed harvesting costs, harvesting may not be optimal in every period.

and other broad-leaf trees.

Thus, we define binary variables δ_t that indicate whether we harvest at a certain time step as

$$\delta_t = \begin{cases} 0, & \text{if } h_{st} = 0 \text{ for all } s, \\ 1, & \text{otherwise.} \end{cases}$$

The fixed harvesting cost are thus given by $\delta_t C_f$. When $\delta_t = 1$ a fixed harvesting cost (in €/ha) occurs and the harvesting intensity $h_{st} \geq 0,\ s = 1, ..., n$ can be freely optimized. When $\delta_t = 0$ both fixed harvesting cost and harvesting amount are zero. The profit obtained from cutting the amount h_t at time t is

$$P_{th}(h_t) = R(h_t) - C_{th}(h_t) - \delta_t C_f,$$

and the profit from a clearcut is

$$P_{cc}(x_t) = R(x_t) - C_{cc}(x_t) - \delta_t C_f.$$

The formulas for computing C_{th} and C_{cc} are given in Appendix A. The net present value of the harvesting strategy is given by

$$f_1(h, x_{t_0}, T) = \frac{-w + \sum_{t=t_0}^{T-1} P_{th}(h_t) b^{\Delta(t+1)} + P_{cc}(x_T) b^{\Delta(T+1)}}{1 - b^{\Delta(T+1)}}, \tag{4}$$

where the length of the rotation period is $T \in [t_0, \infty)$. In addition, the non-negativity conditions $x_{st} \geq 0, h_{st} \geq 0$ must hold for all $t = t_0, ..., T$ and $s = 1, ..., n$. Note that the fixed cost term $\delta_t C_f$ imposes severe discontinuity in the NPV objective function, which makes the optimization difficult to solve with e.g. nonlinear programming and warrants the use of EAs.

The objective function in (4) resembles the classic RF model. However, the choice of rotation period between finite or infinite length is equivalent to the choice between RF and CCF management regimes. The latter is possible by including natural regeneration and thinning in the model. In our work, we approximate the infinite horizon by choosing a sufficiently long rotation period so that any actions beyond become negligible due to discounting.

3.0.2 Carbon Storage

For modeling the carbon storage, we build on [1], but deviate from the therein presented approach in that we do not consider the economic value of CO_2, but the absolute amount of CO_2 in tons. This allows for a more general optimization problem where individual utility functions and nonlinear relationships between money and carbon can be used. The amount of net carbon sequestration (or net negative emissions) in period t can be given as follows:

$$Q_t = \theta\{\widetilde{B}_{t+1}(x_{t+1}) - \widetilde{B}_t(x_t) + D_1(h_t) + D_2(h_t) + D_d(x_t)\} \tag{5}$$

for $t = t_0, ..., T$, where $\widetilde{B}_{t+1}(x_{t+1}) - \widetilde{B}_t(x_t)$ refers to net growth, i.e. the change in biomass between time steps. The additional terms $D_2(h_t)$ and $D_1(h_t)$ are needed to take into account that harvested trees are respectively used for sawlog and pulpwood products, which release their carbon content as they decay. Correspondingly, $D_d(x_t)$ refers to dead tree matter (from natural mortality and harvest residue) and its decay. Formulas for these functions are found in Appendix A based on [1]. Hence, the discounted amount of net negative CO_2 emissions is given by the following objective function:

$$f_2(h, x_{t_0}, T) = \frac{\sum_{t=0}^{T} Q(x_t, h_t) b^{\Delta(t+1)}}{1 - b^{\Delta(T+1)}}. \tag{6}$$

3.0.3 Biodiversity

A forest stand with trees of different size classes is considered more diverse than an even-aged forest. We therefore model biodiversity (per ha) with the Simpson index [29]:

$$d(x_t) = 1 - \frac{\sum_{s=1}^{n} x_{st}(x_{st} - 1)}{\sum_{s=1}^{n} x_{st} \left(\sum_{s=1}^{n} x_{st} - 1 \right)}, \quad d(x_t) \in [0, 1]. \tag{7}$$

The value of the Simpson index is high when the stand carrying capacity is evenly allocated across a great number of species. Note that we set $d(x_t)$ to zero if there are less than ten trees in a forest stand. The discounted value of biodiversity leads to the following objective function:

$$f_3(h, x_{t_0}, T) = \frac{\sum_{t=0}^{T} d(x_t) b^{\Delta(t+1)}}{1 - b^{\Delta(T+1)}}. \tag{8}$$

A similar expression for the biodiversity objective is used in [32].

3.0.4 Optimization Problem

The objective functions for NPV, carbon storage, and biodiversity form the overall optimization problem that is solved to find the Pareto-efficient frontier of optimal trade-offs. Specifically:

$$\max_{\substack{h_{st} \\ s=1,...,n \\ t=t_0,...,T}} \left[f_1(h, x_{t_0}, T), f_2(h, x_{t_0}, T), f_3(h, x_{t_0}, T) \right], \tag{9}$$

subject to (1), (2), and (3), which formally constitutes a constrained multi-objective optimization problem that we plan to handle using MOEAs. The number of variables is 11x the number of time steps we are optimizing for, i.e a 300 year schedule requires 660 decision variables. We next describe the related genetic operators.

4 Methodology

Forest management involves many stakeholders with often conflicting interests. It thus becomes interesting to discover the set of strategies that represents different yet optimal trade-offs. In contrast to earlier research, this study considers economic, environmental, and societal goals simultaneously. In this section, we explore three different MOEAs and define customized evolutionary operators that incorporate domain-specific knowledge.

4.1 Multi-Objective Evolutionary Algorithms

The algorithm at the core of our work must search over $\mathbb{R}^N$ to infer the set of Pareto-optimal forest management strategies that balance economic performance (NPV), carbon storage, and biodiversity. Multi-Objective Evolutionary Algorithms have proven to undertake this search efficiently in many application domains [6]. In this work, we consider three different MOEAs:

- Non-dominated Genetic Algorithm II (NSGA-II [11]), which retains potentially good solutions along the search process based on their front rank and crowding distance.
- Non-dominating Genetic Algorithm III (NSGA-III [10]), which substitutes the crowding distance criterion in NSGA-II with a clustering operator aided by a set of distributed set of reference points.
- Multi-objective Evolutionary Algorithm based on Decomposition (MOEA/D [35]), which decomposes the multi-objective problem into a number of single-objective sub-problems, all solved simultaneously by considering neighborhood information of the produced solution.

Each of these three algorithms will be applied to solve the same optimization problem to uncover the Pareto-efficient frontier of optimal forestry policies. For all three algorithms, we use the pymoo implementations from [3].

4.2 Customized Operators

We define customized variables $\widehat{h}_{st}$ such that $\widehat{h}_{st} = h_{st}/x_{st}$, which is the fraction of trees harvested at time step t in size class s. It is convenient to express the variables in relative amounts as constraint (3) can then be expressed as $0 \leq \widehat{h}_{st} \leq 1$ for all s, t. Any solution that satisfies this is feasible. We denote the harvesting amounts at time step t by $h_t = (h_{1t}, h_{2t}, \ldots, h_{St})$, where S is the number of size classes.

To create a random initial solution, we choose $\widehat{h}_t$ such that for each t, we have $\widehat{h}_t = 0$ with probability p_0; otherwise, each component of $\widehat{h}_t$ is drawn independently from the uniform distribution. The parents for recombination are chosen using the binary tournament selection operator. We *customize* two different crossover operators and one mutation operator to create an offspring population. For the first crossover operator, we randomly choose two parents $(h^{(1)}, h^{(2)})$, each a matrix of integers, to create two offspring solutions $(c^{(1)}, c^{(2)})$. With crossover probability p_x, we draw a crossover point t_x uniformly from $t_0, \ldots, T$ and create the offspring, as presented below:

$$\left(c_t^{(1)}, c_t^{(2)}\right) = \begin{cases} \left(h_t^{(1)}, h_t^{(2)}\right), & \text{if } t < t_x, \\ \left(h_t^{(2)}, h_t^{(1)}\right), & \text{if } t \geq t_x. \end{cases}$$

This is similar to 1-point binary crossover, but instead of swapping the tails of binary strings, we swap the bottoms of matrices. The numerical values are not changed in the first crossover, they are just swapped between solutions.

The second crossover operator does, however, affect the numeric values in the solution matrices. As before, we denote the parents by $(h^{(1)}, h^{(2)})$. The offspring $(c^{(1)}, c^{(2)})$ is formed as outlined in Algorithm 1. If both of the parent solutions have non-zero harvesting amounts at a certain time step, then the corresponding offspring vectors are formed using Simulated Binary Crossover (SBX) [9] between the parent vectors; otherwise, the offspring is created by randomly picking $h_t^{(1)}$ or $h_t^{(2)}$ with 50% probability. This ensures a high number of time steps without any harvesting activities, as fixed costs usually render too frequent harvesting sub-optimal.

Algorithm 1 The second crossover operator. The spread parameter η_c for SBX has the value 2.0.

for $t \in \{1, \ldots, T\}$ **do**
  if $h_t^{(1)}, h_t^{(2)} > 0$ **then**
    form vectors $c_t^{(1)}, c_t^{(2)}$ by component-wise SBX
  else
    $c_t^{(i)} \leftarrow \begin{cases} h_t^{(1)} & \text{with probability } \frac{1}{2} \\ h_t^{(2)} & \text{with probability } \frac{1}{2} \end{cases}$ for $i = 1, 2$
  end if
end for

The customized mutation operator creates one offspring solution from one parent solution according to Algorithm 2. The distribution D in the algorithm is used to create random harvesting strategies for a single time step. Drawing from the distribution D is done by uniformly choosing a point $h_t \in \{2, \ldots, 7\}$ and setting

$$c_{st} = \begin{cases} 0, & \text{if } s < h_t, \\ 1, & \text{otherwise.} \end{cases}.$$

With a certain probability we replace all zero vectors with random non-zero vectors and vice versa. Otherwise we apply component-wise polynomial mutation [8] to a non-zero vector; a zero vector is left untouched.

In the recombination phase of the MOEA, one half of the offspring is generated using the first crossover operator, the other half via the second crossover operator. The

Algorithm 2 Mutation operator. Let h be the parent and c be the child. The spread parameter η_c for polynomial mutations is 20.0 and probability 1/11. The parameter p_{mut} has the value 0.05.

---

for $t \in \{1, \ldots, T\}$ **do**
  draw r from Unif[0,1]
  if $r < p_{\text{mut}}$ **then**
    if $h_t > 0$ **then**
      $c_t \leftarrow 0$
    else
      draw c_t from the distribution D
    end if
  else
    if $h_t > 0$ **then**
      $c_t \leftarrow$ component-wise polynomial mutation of p_t
    else
      $c_t \leftarrow 0$
    end if
  end if
end for

---

algorithm is terminated after a fixed number of generations has elapsed.

5 Results

Our results section consists of four different, albeit related parts. First, we compare the performance of three MOEAs: NSGA-II, NSGA-III, and MOEA/D. As the true reference front (i.e. a Pareto-optimal strategy) is unknown, we use the hypervolume indicator [37] as a guidance criterion for comparing solutions from different MOEAs [17, 36], and for choosing the best performing algorithm for further experiments. Second, we use the best-performing MOEA for finding the entire set of Pareto-optimal solutions. We visualize the Pareto front, and discuss its shape and implications for the trade-offs between the three objectives. Thirdly, we analyze the dominant strategies to unveil salient knowledge about what solution properties makes a solution optimal. This process of "innovization", a by-product of performing multi-objective optimization, is an important process of knowledge discovery [13] in real-world problems. We choose individual solutions from different parts of the Pareto front and make qualitative observations regarding the corresponding harvesting schedules. Finally, we demonstrate the use of a *trade-off* analysis – rarely performed in EMO application studies – to choose a single preferred solution from the obtained MOEA solutions.

5.1 Comparison of MOEAs

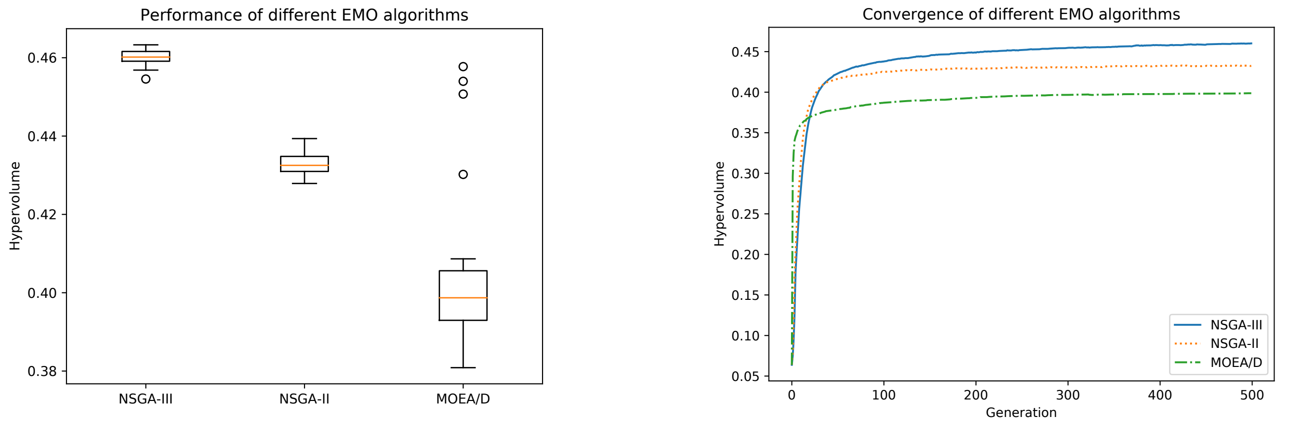
In the following we compare the performance of three well-known MOEAs: NSGA-II, NSGA-III and MOEA/D. We have run each algorithm 20 times from different initial populations on the multi-objective forest management problem. The optimization was run for 60 time steps (corresponding to a 300-year horizon). For each algorithm, the population size was set to $1,000$ and and the number of generations to 500 which results in a total 500,000 function evaluations. The evaluation of each solution through the simulation models described in Equations 1 and 2 is fast and allowed us to consider such a large number of solution evaluations. The MOEA/D-specific parameters size of neighborhood and probability of mating were 200 and 0.5, respectively. These parameters are set according to suggestions provided in their original studies.

Figure 2a shows the statistics of the resulting hypervolume metrics across all algorithms and runs in a boxplot. In this comparison, clearly, NSGA-III shows the most robust performance, with the highest hypervolume value and the lowest variance. NSGA-II and MOEA/D perform worse and are not able to obtain good performance on average. In addition to evaluating the goodness of the obtained set of non-dominated solutions, the convergence over time and therefore the performance at each generation are analyzed next. Figure 2b shows the performance of the median run for each algorithm. Interestingly, NSGA-II and MOEA/D show a slightly better performance than NSGA-III in the beginning. However, from generation 50 (after about 50,000 solution evaluations), NSGA-III clearly outperforms the others. With higher solution evaluations, NSGA-III's performance becomes relatively better.

The superiority of NSGA-III can be attributed to its guidance of the search through reference directions in combination with the hyperplane-based normalization concept. NSGA-II's crowding distance approach is known to perform not very well for more than two objectives and MOEA/D's normalization considers only the ideal but not the nadir point in the objective space. Our experiment indicates that both – the usage of reference directions and a suitable normalization – is of importance to obtain a diverse set of non-dominated solutions for the proposed forest management problem.

5.2 Non-dominated Set of Solutions

Next, we present the non-dominated solutions obtained by the best performing algorithm for the forest management problem – NSGA-III – for further investigations. Moreover, we address the underlying randomness of MOEAs by merging solutions from 10 independent runs together to demonstrate the solution properties of multiple runs. We run each optimization for each horizon lengths between 15 to 60, with 5 step intervals. We consider the 60-step solution (300 years) to be equivalent to a continuous-cover solution due to the strong discounting effect. The objective vectors (or points) of the resulting non-dominated set of solutions is shown in Figure 3.



(a) Boxplot showing the statistics of hypervolume of each MOEA.

(b) Hypervolume at each generation for a median run of each MOEA.

Figure 2: Comparison of NSGA-II, NSGA-III or MOEA/D using hypervolume metric.

It is interesting to note that NSGA-III is able to handle objective values of different orders of magnitude to find representative solution with a good diversity. The non-dominated set of solutions mostly consist of strategies with long time horizons (green dots), suggesting that continuous-cover forestry is optimal as soon as a balance between profit, carbon storage, and biodiversity is preferred. Only an extreme focus on profit-maximization leads to RF strategies with short rotation periods (blue crosses), but naturally results in poor values for biodiversity. The Pareto front visualizes how sacrificing profit ever so slightly leads to a paradigm shift from RF to CCF. These results concur with earlier studies (see e.g. [32]) that found CCF to be the preferred strategy when additional non-profit objectives are considered.

Table 1: The objective values for five chosen solutions

Soln.	Econ. value (€/ha)	C-Storage (ton/ha)	Biodiversity
A	3240	44.4	2.21
B	189	84.2	2.62
C	1939	67.8	2.53
D	3216	46.6	2.48
E	1792	59.1	2.60
Minimum	-713	30.8	2.21
Maximum	3252	85.8	2.72

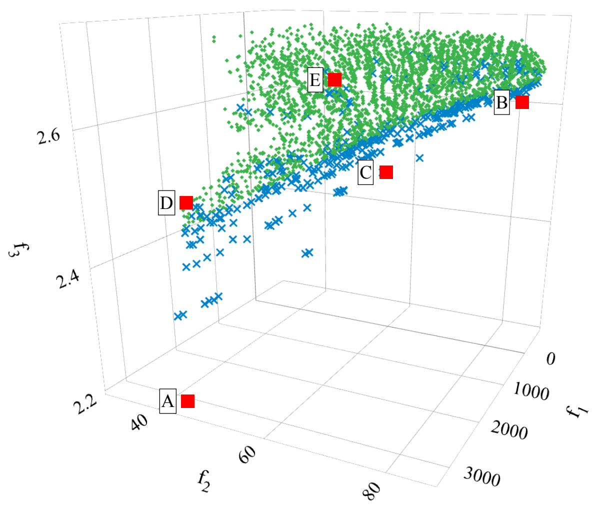


Figure 3: The NSGA-III front with all non-dominated forest management strategies. Clear-cut RF strategies are marked as blue crosses, CCF as green dots. Economic value (€/ha), carbon storage (ton/ha), and biodiversity are denoted as f_1, f_2, and f_3, respectively.

5.3 Analysis of Harvesting Schedules

Individual preferences for the three objectives will clearly affect the choice of a single preferred harvesting schedules, but before any such post-optimality analysis is performed, solutions from different parts of the obtained front must be well understood.

Strategies A and D both emphasize economic value and lead to similar values for carbon storage. The two strategies differ, however, significantly in their values for biodiversity. The detailed harvesting schedules in Figure 4 reveal that A and D both perform frequent thinning. Solution A, however, is a RF strategy with fairly short rotation length and clear-cuts at the end of each harvesting schedule. Solution D still leads to a high profit, but uses continuous cover forestry. The comparison between A and D demonstrates how clear-cutting and short rotation periods considerably reduce a forest's biodiversity, while only adding a disproportionately small gain in profit. This observation may help policy makers to justify a paradigm shift away from ecologically harmful clear-cut harvesting and towards sustainable CCF forestry.

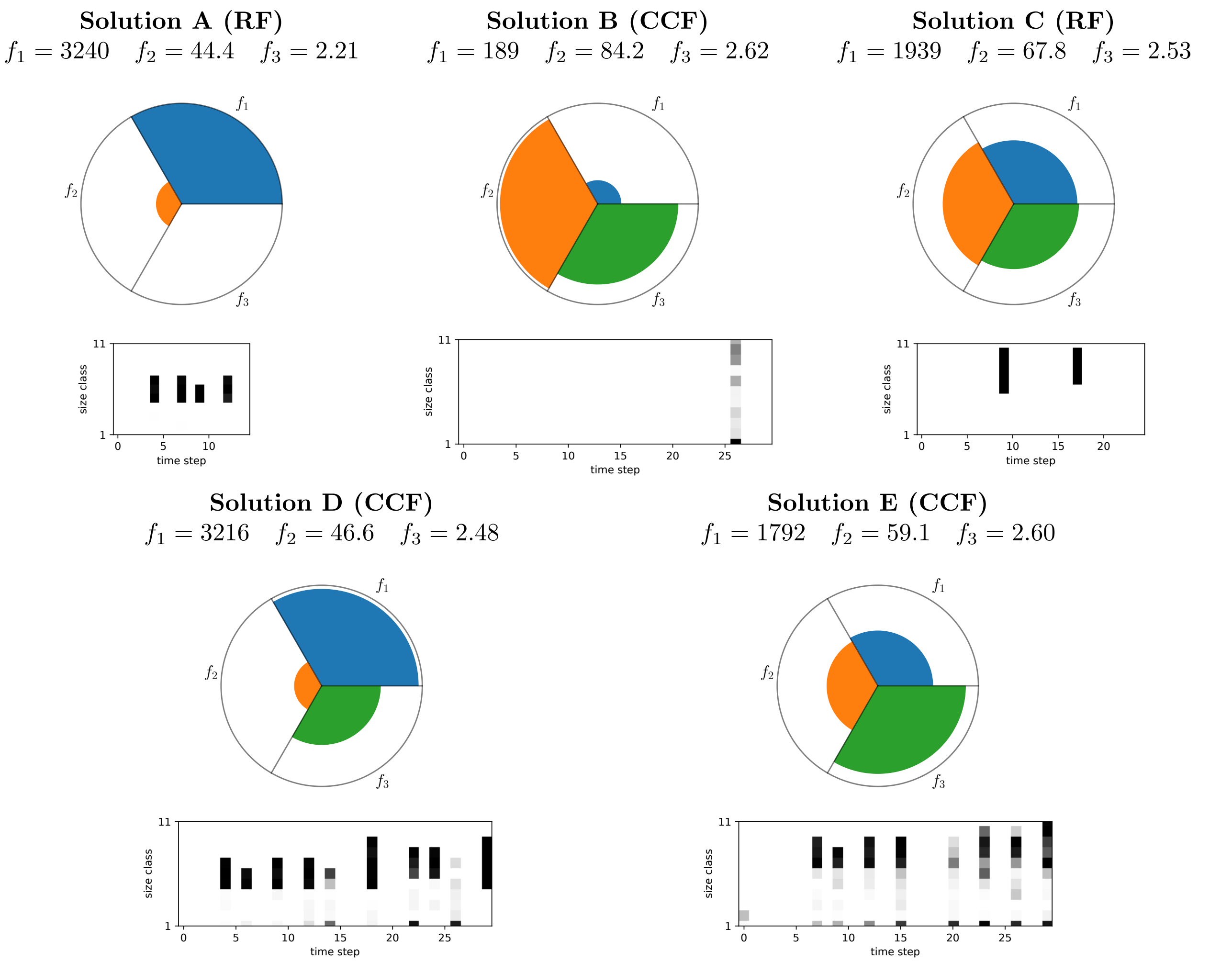


Figure 4: Illustration of the five exemplary chosen solutions. The objective space is visualized by petal diagrams and the design space by the respective harvesting schedules. Strategies shorter than 30 time steps (A, C) indicate a finite horizon length corresponding to RF. For strategies longer than 150 years, approximating continuous cover forestry (B, D, E), only the first 30 time steps are shown.

In stark contrast, solution B provides high values for both carbon storage and biodiversity. Only *one* harvest occurs during the first 150 years. Leaving the forest untouched allows the accumulation of dead wood that binds massive amounts of CO_2, but leads - quite understandably - to a low economic output.

Solution C provides a trade-off between carbon storage and economic value. Less emphasis was put on biodiversity, which lead to a RF strategy using clear-cutting. However, compared to the pure profit-maximizing strategy A, the profit-carbon trade-off in C leads to the harvest of bigger trees, and less frequent thinning and clear-cuts. The harvesting schedule corresponding to strategy C may provide an acceptable compromise to the case of Finland, given in Section 1, where policy makers have to find a profit-carbon trade-off that balances economic concerns with ambitious emission goals.

Finally, solution E represents a balanced trade-off between profit, carbon storage, and biodiversity. This is similar to C, but also considers biodiversity an important dimension. This leads to a shift from RF to CCF, less frequent thinning and a focus on bigger trees.

5.4 Sytematic Selection of a Preferred Solution

Clearly, the obtained non-dominated set does not have a uniformly distributed set of points in the entire front. While in most part, the variation of objective vectors is smooth and small, in certain other parts, they change abruptly. But importantly, every non-dominated point makes a trade-off among the three objectives and thus is a viable candidate for final adoption. Thus, the next important step in an applied multi-objective optimization task is the issue of choosing a single preferred solution from a large number of obtained non-dominated solutions.

Any such decision-making must involve all objectives and real decision-makers with certain preference information. We emphasize here that choosing a preferred single solution from 3,280 solutions shown in Figure 3 is not an easy task. More studies on applied MOEA should provide systematic procedures for achieving the decision-making task. Here, we provide one particular procedure that we adopted for this study.

First, we attempt to choose a few (say, K) solutions from the entire non-dominated set. Ideally, a clustering strategy can be employed to pick well-distributed K solutions from the obtained MOEA set. Preference information for biasing certain objectives can also be applied here in consultation with forest department decision-makers and stake-holders, but here we simply choose five ($K = 5$) well-distributed solutions manually, as indicated by red squares in Figure 3. Table 1 presents the respective objective vectors and also indicates the minimum and maximum objective values of the entire obtained non-dominated set, indicating the respective nadir and ideal objective vectors, respectively. Other multi-criterion decision-making (MCDM) methods such as Pareto-race [18], NIMBUS [23], surrogate-worth analysis [5], self-organizing maps [25], and others [24] can be used here to pick K solutions.

Second, we analyze the chosen K preferred solutions to understand their trade-off, which can be defined in different ways. Here, we define the trade-off of a solution by first identifying its neighboring chosen points and then averaging the maximum ratio of the sacrifice to gain in moving from $\mathbf{x}$ to its neighbors. The trade-offs in the objective space and the corresponding harvesting schedules of the chosen five solutions are visualized in more detail in Figure 4. The petal plots of these solutions indicate the relative change of objectives between any two solutions. For example, solution A is the neighbor of solution D. A comparison of the two respective petal plots indicate that a large sacrifice of objective f_3 from D to A occurs for a tiny gain in objective f_1. The whole green f_3 is missing in solution A, whereas a tiny part of blue region is missing in solution D. Thus, D may be preferred compared to A from a trade-off analysis, as a relatively large sacrifice for a small gain will be considered favorable for choosing a solution. To systematize the trade-off calculation, we tabulate the trade-off value for each of the five solutions (say i-th one: $\mathbf{x}^{(i)}$) with each of the neighbors ($\mathbf{x}^{(j)} \in B(\mathbf{x}^{(i)})$) in Table 2 using the following equation [28]:

$$R(\mathbf{x}^{(i)}, \mathbf{x}^{(j)}) = \frac{\text{Loss}_f(\mathbf{x}^{(i)} \rightarrow \mathbf{x}^{(j)})}{\text{Gain}_f(\mathbf{x}^{(i)} \rightarrow \mathbf{x}^{(j)})}. \tag{10}$$

For example, the trade-off value of solution D with respect to its neighboring solution A is 16.464 – a large value. The final averaged trade-off value ($\bar{R}(\mathbf{x}^{(i)}) = \sum_{j\in B(\mathbf{x}^{(i)})} R(\mathbf{x}^{(i)}, \mathbf{x}^{(j)})/|B(\mathbf{x}^{(i)})|$) indicates that solution D is the winner. A detailed look at Figure 3 will reveal that solution D acts as a 'knee' point in the obtained set of points, which – if it exists – is usually one of the most preferred solutions in a Pareto-optimal front. It is interesting to see how our systematic trade-off analysis is able to identify the preferred point.

Ultimately, there is no single correct strategy for choosing a single preferred solution and whatever course of actions is chosen will depend on personal preferences. However, by framing forest management as a multi-objective optimization problem it becomes possible to highlight the trade-offs between objectives, which in turn may help decision makers to find a strategy that best combines different stakeholder interests.

6 Conclusions

In this study, we have explored the use of multi-objective evolutionary algorithms (MOEAs) for finding sustainable forest management strategies through a multi-objective formulation. Specifically, we have analyzed the trade-offs between three different objectives: economic profit, carbon storage, and biodiversity. We have visualized the Pareto-front consisting of a number of non-dominated forest policies and have chosen five example solutions for which we have also discussed their trade-offs in the objective space. Furthermore, we have performed an innovization analysis for which we have provided detailed harvesting schedules of the example solutions in the design space.

The NPV objective function, formulated here, poses a particular challenge due to discontinuities that are introduced by a mix of fixed and variable harvesting costs. Since MOEA have shown to overcome even these challenging issues, we can use the proposed method also with alternative objectives. For example, one may argue that the price for carbon is usually fixed and cannot be freely optimized. We can swap carbon storage with different goals while keeping the methodological framework the same. For future work, it may be interesting to analyze and optimize the deadwood mass in forests, which has been shown to store significant amounts carbon.

Our work represents the first proof-of-concept study that MOEAs can be very useful for solving the century old problem of how to optimally manage our precious forest resources. Our proposed MOEA approach not only helps decision-makers in finding an optimal strategy, but it also prescribes detailed harvesting schedules to forest managers who can implement the chosen strategy in practice.

Table 2: Trade-off for each of the five chosen solutions using their neighbors.

$\mathbf{x}$	Neigh. $B(\mathbf{x})$	A	B	C	D	E	Trade-off $\bar{R}(\mathbf{x})$
A	C,D	-	-	0.336	0.061	-	0.199
B	C,E	-	-	1.053	-	1.190	1.122
C	A,B,D,E	2.976	0.950	-	1.486	1.233	1.661
D	A,C,E	16.464	-	0.673	-	0.793	**5.977**
E	B,C,D	-	0.840	0.811	1.262	-	1.090

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